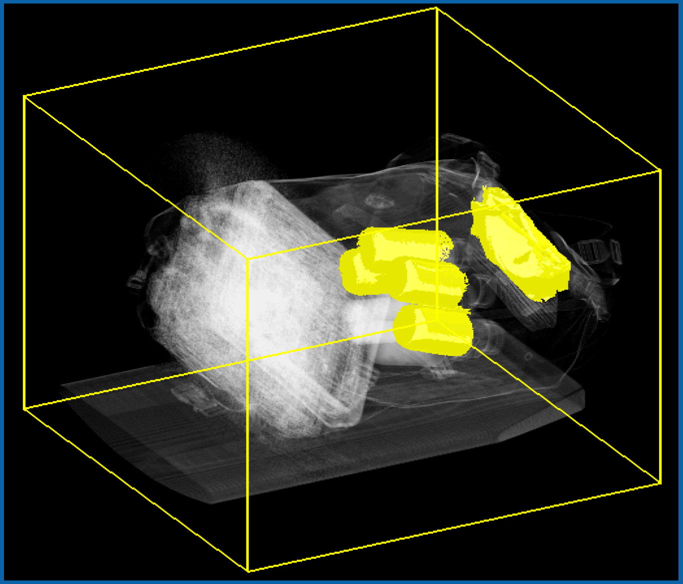
Coupled Segmentation of Industrial CT Images

Peer-Timo Bremer, Kyle Champley, Jeff Kalmann, Hyojin Kim, Karina Bond, Jayaraman J. Thiagarajan, Eric Wang, Harry Martz

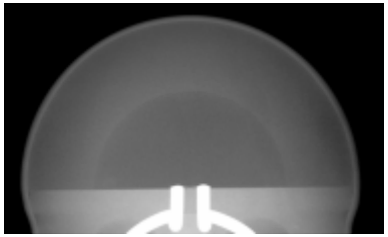


This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344. LLNL-PRES-654650

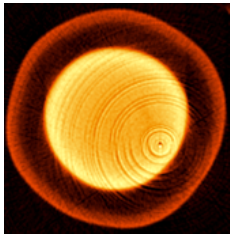
Industrial X-Ray Image Segmentation is a Key Component in Many Applications Crucial to LLNL and National Security

- Non-Destructive Evaluation (NDE) is an integral component in many of Livermore's mission critical areas:

WCI

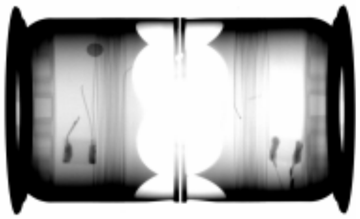


Stockpile Stewardship



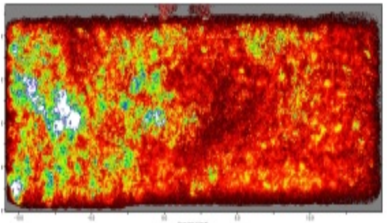
Nuclear Fuel

NIF



Hohlraum Target

PLS



Material Characterization

GS

Transportation Security

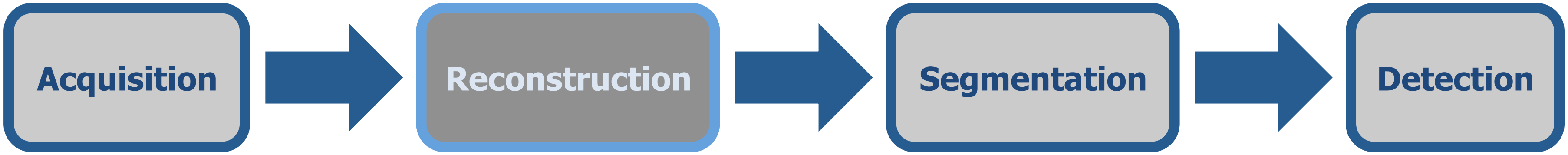
- **Goal:** Identify objects, materials, and/or features in a noisy, cluttered, and compromised environment
- **Challenge:** Current solutions are highly application dependent and often inadequate

Industrial NDE Faces a Number of Interconnected Challenges such as Noise, Artifacts, and Lack of Resolution

Acquisition → **Reconstruction** → **Segmentation** → **Detection**

- Data acquisition is limited by cost, time, energy spectrum, etc.

Industrial NDE Faces a Number of Interconnected Challenges such as Noise, Artifacts, and Lack of Resolution



- Data acquisition is limited by cost, time, energy spectrum, etc.
- Artifacts in the reconstruction, e.g., streaks, cupping, beam hardening

Industrial NDE Faces a Number of Interconnected Challenges such as Noise, Artifacts, and Lack of Resolution

Acquisition → **Reconstruction** → **Segmentation** → **Detection**

- Data acquisition is limited by cost, time, energy spectrum, etc.
- Artifacts in the reconstruction, e.g., streaks, cupping, beam hardening
- Inaccurate segmentations, e.g., merged or split objects , partial volume, unreliable material estimation

Industrial NDE Faces a Number of Interconnected Challenges such as Noise, Artifacts, and Lack of Resolution

Acquisition → **Reconstruction** → **Segmentation** → **Detection**

- Data acquisition is limited by cost, time, energy spectrum, etc.
- Artifacts in the reconstruction, e.g., streaks, cupping, beam hardening
- Inaccurate segmentations, e.g., merged or split objects , partial volume, unreliable material estimation
- Inconsistent detection causing both false positive and false negative results

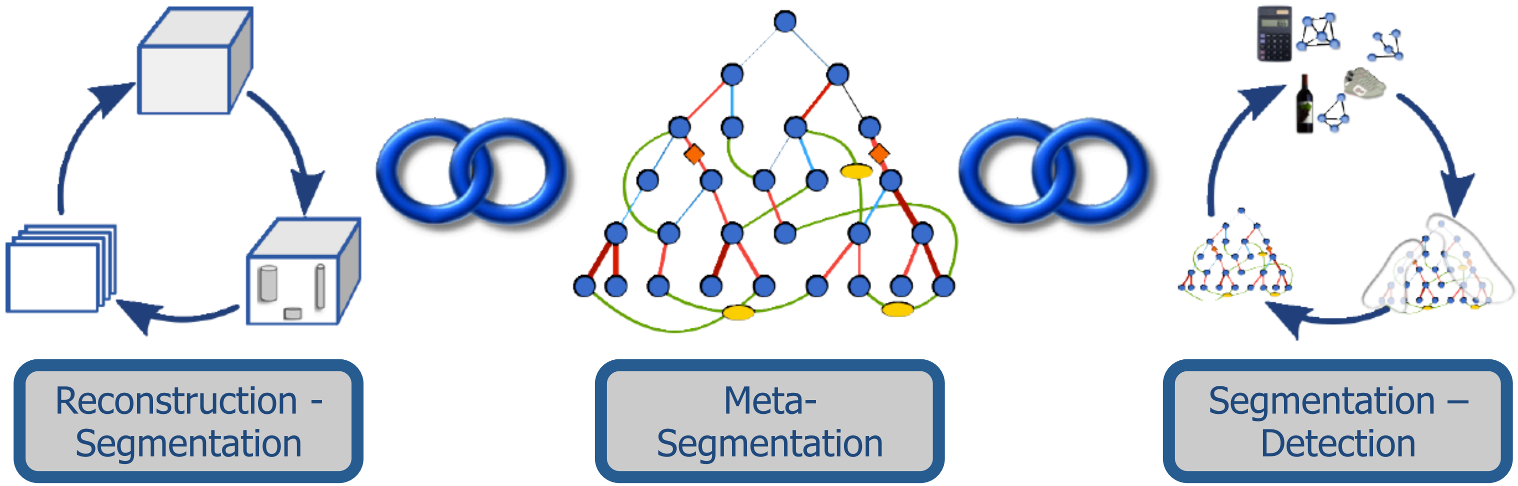
Industrial NDE Faces a Number of Interconnected Challenges such as Noise, Artifacts, and Lack of Resolution

Acquisition → **Reconstruction** → **Segmentation** → **Detection**

- Data acquisition is limited by cost, time, energy spectrum, etc.
- Artifacts in the reconstruction, e.g., streaks, cupping, beam hardening
- Inaccurate segmentations, e.g., merged or split objects , partial volume, unreliable material estimation
- Inconsistent detection causing both false positive and false negative results

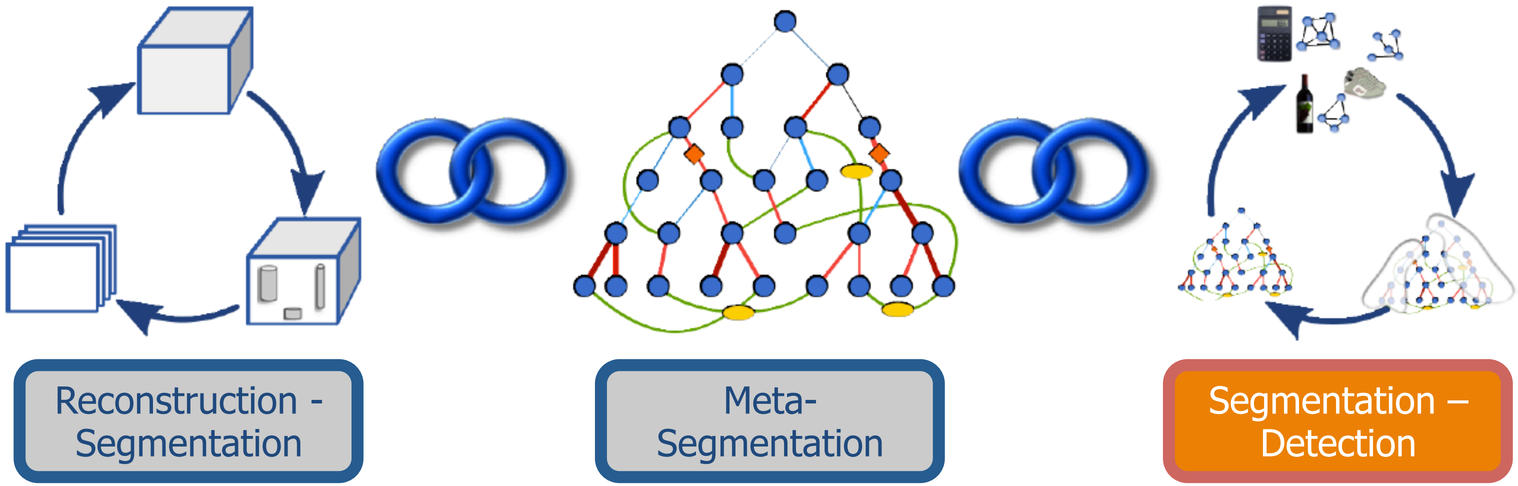
Current techniques tackle each stage independently

This Project Integrates the Pipeline by Focusing on Feedback Loops Between Stages



- Reconstruction – Segmentation:
  - Partial segmentations can enhance the reconstruction
- Segmentation – Detection:
  - Semantic knowledge can enhance the segmentation
  - Previous results can disambiguate difficult cases

This Project Integrates the Pipeline by Focusing on Feedback Loops Between Stages



- Reconstruction – Segmentation:
  - Partial segmentations can enhance the reconstruction
- Segmentation – Detection:
  - Semantic knowledge can enhance the segmentation
  - Previous results can disambiguate difficult cases

Segmentation and Detection Appear Distinct and Often Apply Very Different Classes of Techniques

- Segmentation: Finding coherent regions in the image
  - Edge detection
  - Region growing or splitting
- Detection: Finding objects or configuration of objects
  - Semantic features, e.g., volume, shape, material
  - Classifiers based on training data

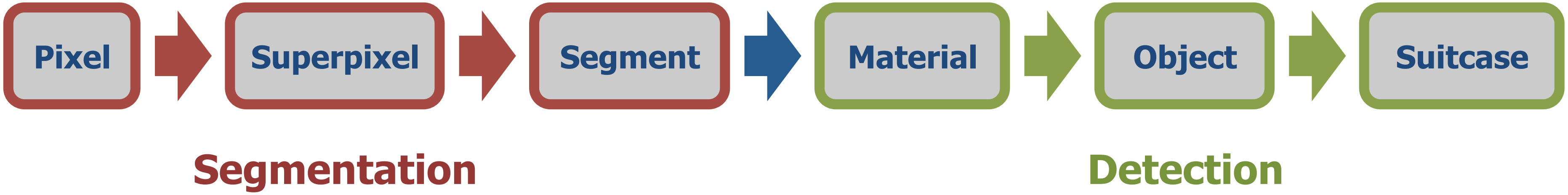
Segmentation and Detection Appear Distinct and Often Apply Very Different Classes of Techniques

- Segmentation: Finding coherent regions in the image
  - Edge detection
  - Region growing or splitting
- Detection: Finding objects or configuration of objects
  - Semantic features, e.g., volume, shape, material
  - Classifiers based on training data
- Instead these stages simply represent a convenient separation of a continuous spectrum of techniques

Pixel → Superpixel → Segment → Material → Object → Suitcase

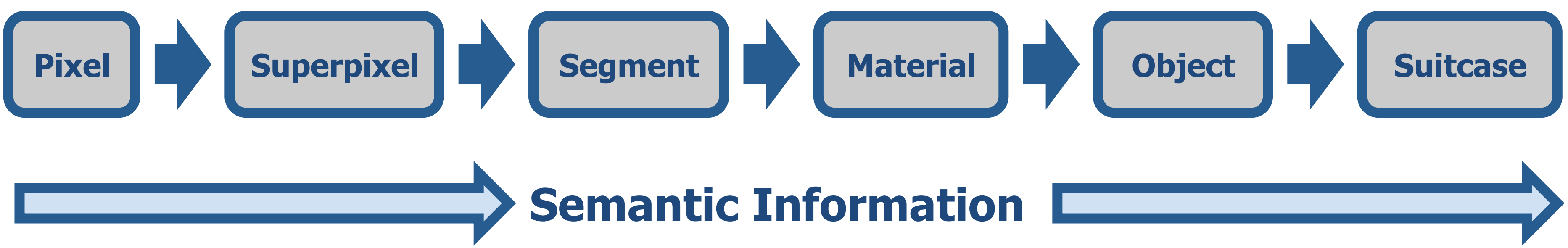
Segmentation and Detection Appear Distinct and Often Apply Very Different Classes of Techniques

- Segmentation: Finding coherent regions in the image
  - Edge detection
  - Region growing or splitting
- Detection: Finding objects or configuration of objects
  - Semantic features, e.g., volume, shape, material
  - Classifiers based on training data
- Instead these stages simply represent a convenient separation of a continuous spectrum of techniques



Segmentation and Detection Appear Distinct and Often Apply Very Different Classes of Techniques

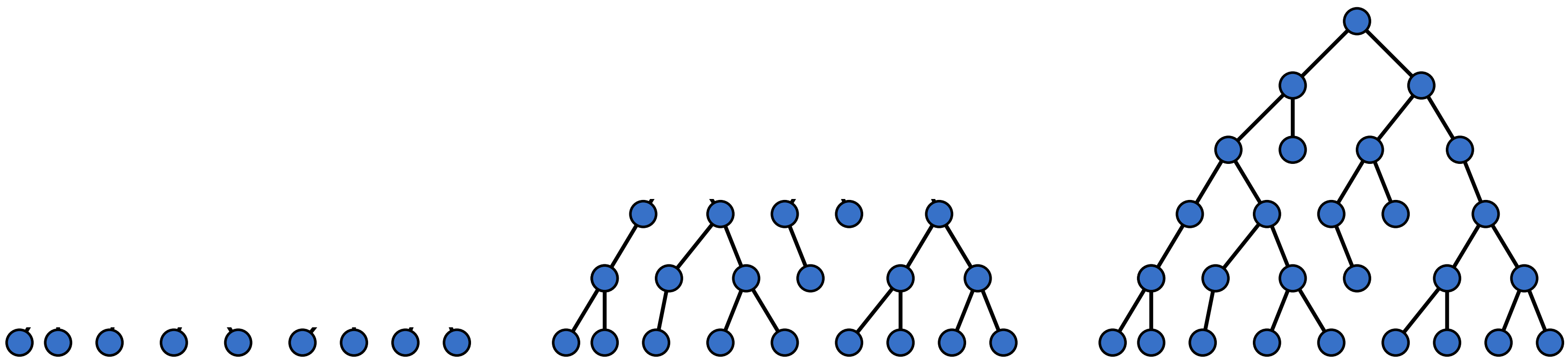
- Segmentation: Finding coherent regions in the image
  - Edge detection
  - Region growing or splitting
- Detection: Finding objects or configuration of objects
  - Semantic features, e.g., volume, shape, material
  - Classifiers based on training data
- Instead these stages simply represent a convenient separation of a continuous spectrum of techniques



Segmentation and Detection Appear Distinct and Often Apply Very Different Classes of Techniques

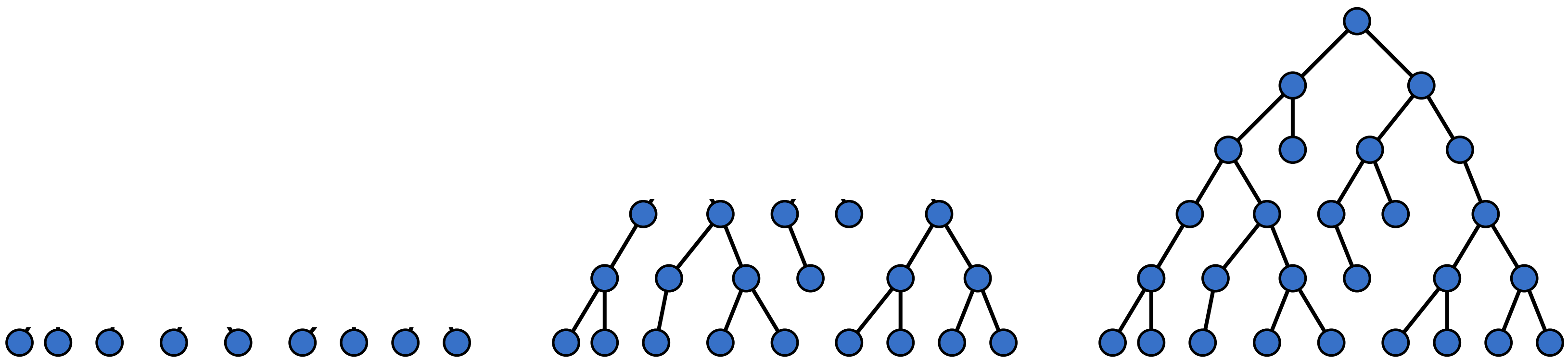
- Segmentation: Finding coherent regions in the image
  - Edge detection
  - Region growing or splitting
- Detection: Finding objects or configuration of objects
  - Semantic features, e.g., volume, shape, material
  - Classifiers based on training data
- Instead these stages simply represent a convenient separation of a continuous spectrum of techniques

Bottom-Up Image Segmentation Successively Merges Elements to Form a Hierarchy of Segments



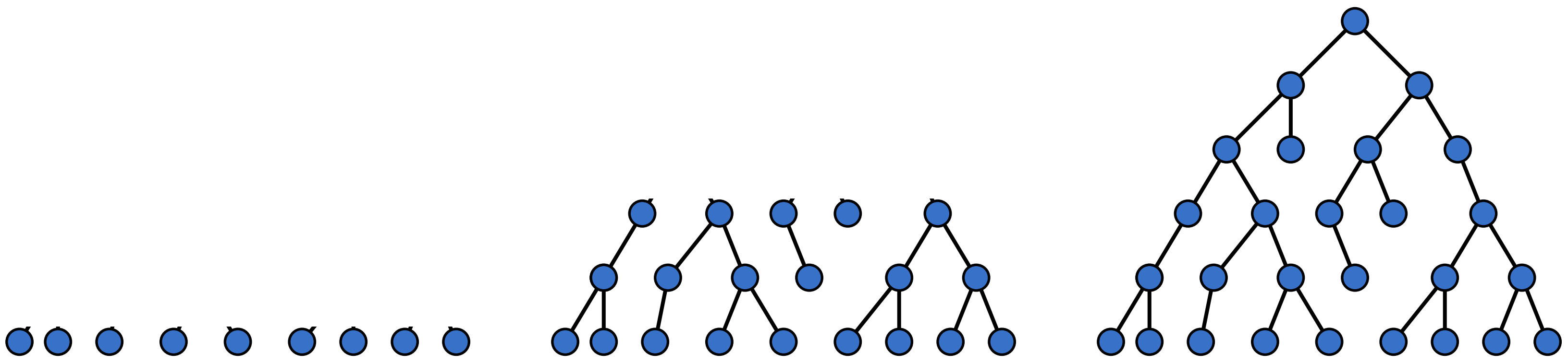
- Challenges:
  - Feature selection: How to determine candidate merges
  - Merge order: Which elements to merge first
  - Stopping criterion: What defines a *segment*

Bottom-Up Image Segmentation Successively Merges Elements to Form a Hierarchy of Segments



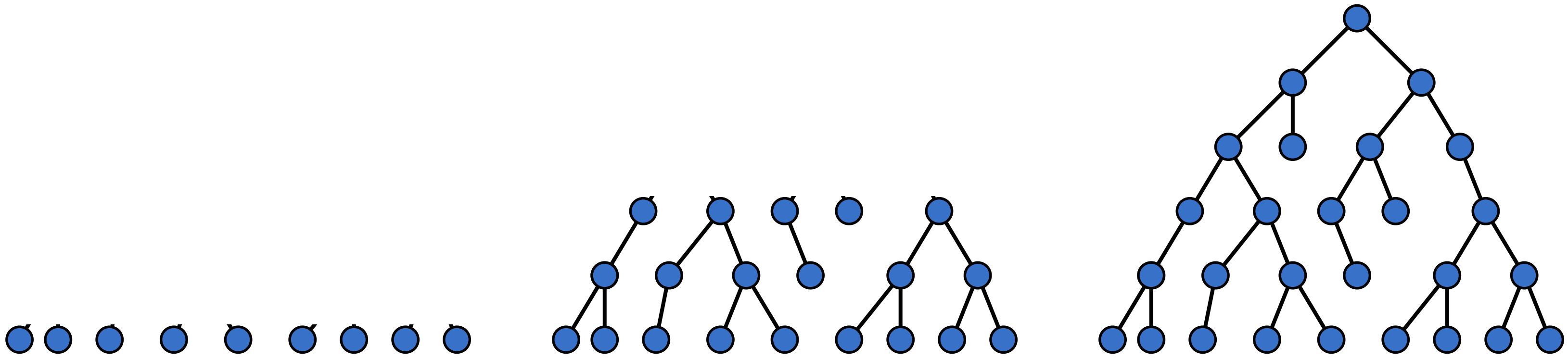
- Challenges:
  - Feature selection: How to determine candidate merges
  - Merge order: Which elements to merge first
  - Stopping criterion: What defines a *segment*

Bottom-Up Image Segmentation Successively Merges Elements to Form a Hierarchy of Segments



- Challenges:
  - Feature selection: How to determine candidate merges
  - Merge order: Which elements to merge first
  - Stopping criterion: What defines a *segment*
- Problems with merge order and stopping criteria are due to missing semantic information leading to irreversible errors in the hierarchy

Bottom-Up Image Segmentation Successively Merges Elements to Form a Hierarchy of Segments

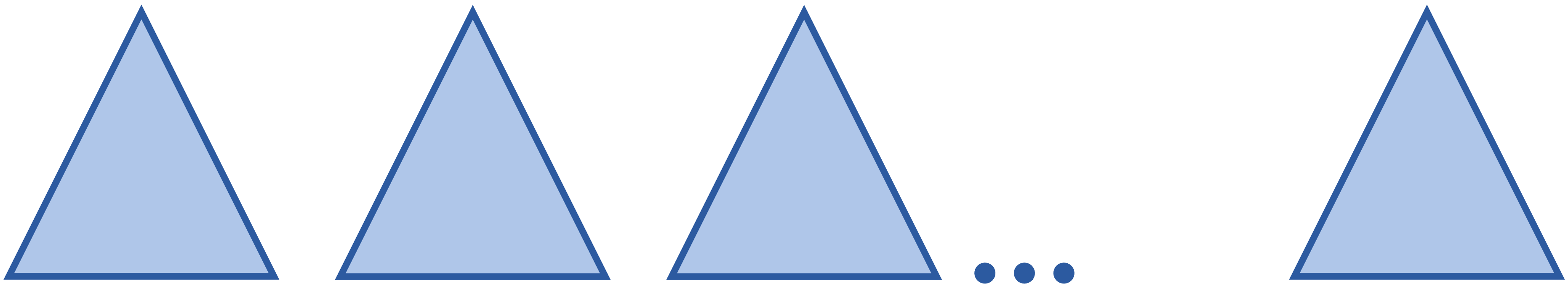


- Challenges:
  - Feature selection: How to determine candidate merges
  - Merge order: Which elements to merge first
  - Stopping criterion: What defines a *segment*
- Problems with merge order and stopping criteria are due to missing semantic information leading to irreversible errors in the hierarchy

Avoid binding choices by exploring all potential hierarchies

Create Multiple Randomized Hierarchies to Explore the Space of Potentially Useful Segmentations

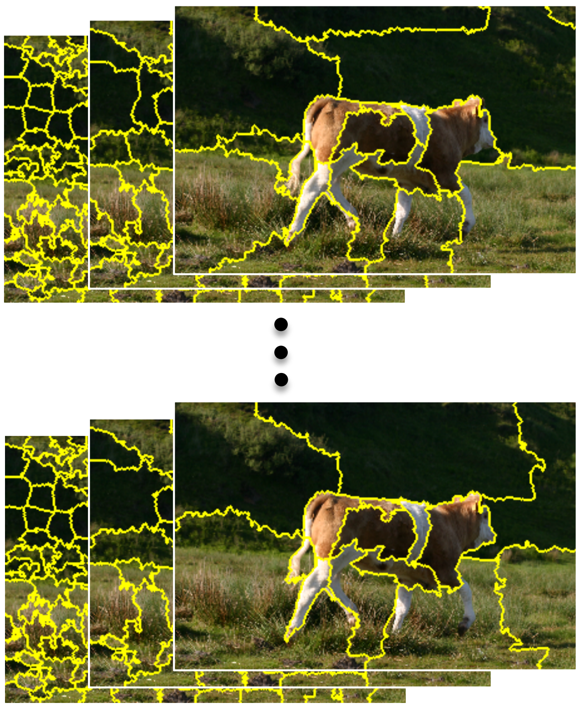
- Randomize the merge order to account for unavoidable mistakes



- Choose the "best" segments (not segmentations) based on:
  - Consensus
  - Labeled training data
  - Unsupervised learning

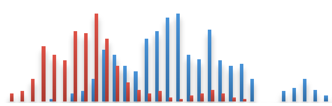
Multi-Hierarchy Consensus of Natural Images Produces Superior Results Across A Wide Range of Scenes

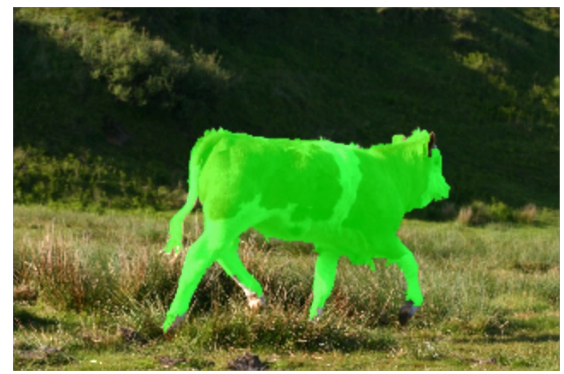
Building Multiple Hierarchies → **Consensus Inference** → **Segmentation using Graph Cuts**



[Weighted Consensus from Multiple Hierarchies]

Model Foreground and Background Regions of Interest





Guided Segmentation of Luggage Scans Using Training Data of Multiple Threat Classes

- Find and classify multiple different threats in a collection of bags scanned by the ALERT Center at Northeastern University
- Data: ~100 Scans containing:
  - Background: clothes, water, books, etc.
  - Threats: Saline solution, modeling clay, rubber sheets
  - Pseudo-threats: threat materials in small quantities
- Challenge: Improve segmentation of threat objects using labeled training data

Guided Segmentation of Luggage Scans Using Training Data of Multiple Threat Classes

- Find and classify multiple different threats in a collection of bags scanned by the ALERT Center at Northeastern University
- Data: ~100 Scans containing:
  - Background: clothes, water, books, etc.
  - Threats: Saline solution, modeling clay, rubber sheets
  - Pseudo-threats: threat materials in small quantities
- Challenge: Improve segmentation of threat objects using labeled training data

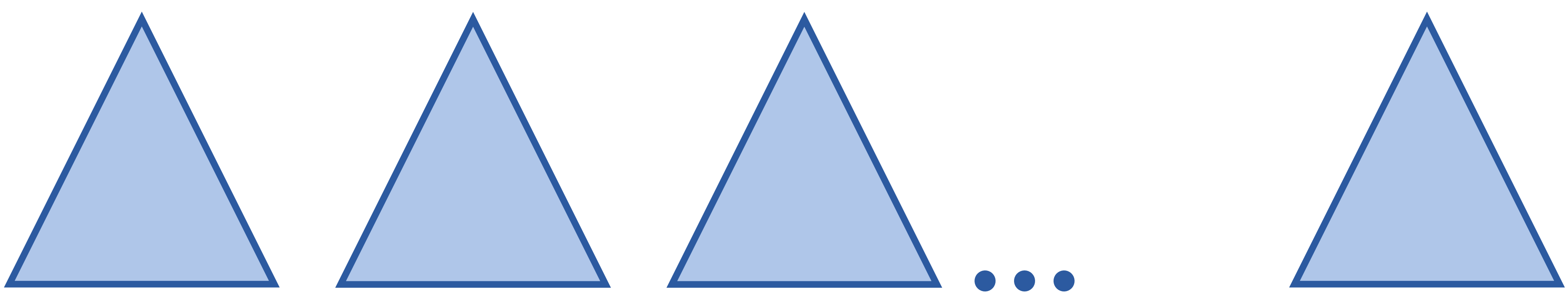
Can you better segment a water bottle because you have seen other bottles

Integrate Multiple Hierarchies with a Trained Threat Classifier to Construct per Class Consensus Segmentation

- Train threat classifier using labeled data and a set of custom designed features, e.g., histograms, shape, volume, etc.

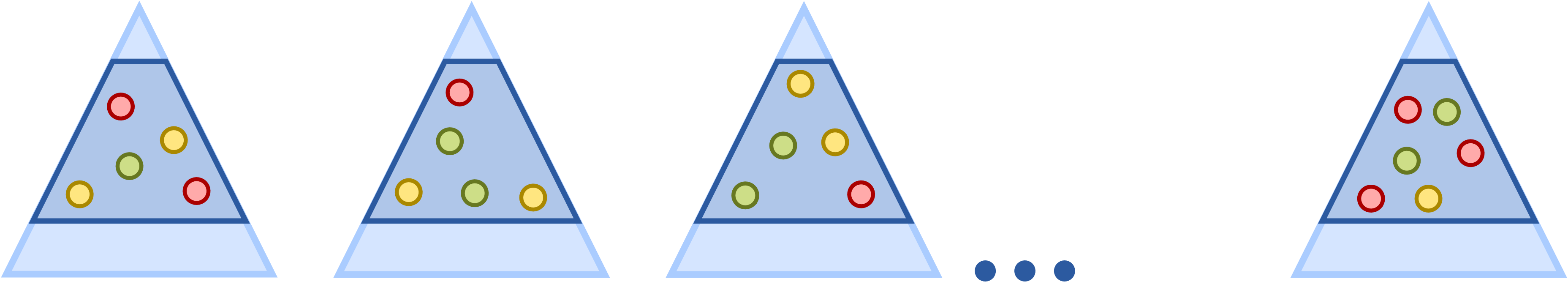
Integrate Multiple Hierarchies with a Trained Threat Classifier to Construct per Class Consensus Segmentation

- Train threat classifier using labeled data and a set of custom designed features, e.g., histograms, shape, volume, etc.
- Construct multiple hierarchical segmentations by randomizing the merge order



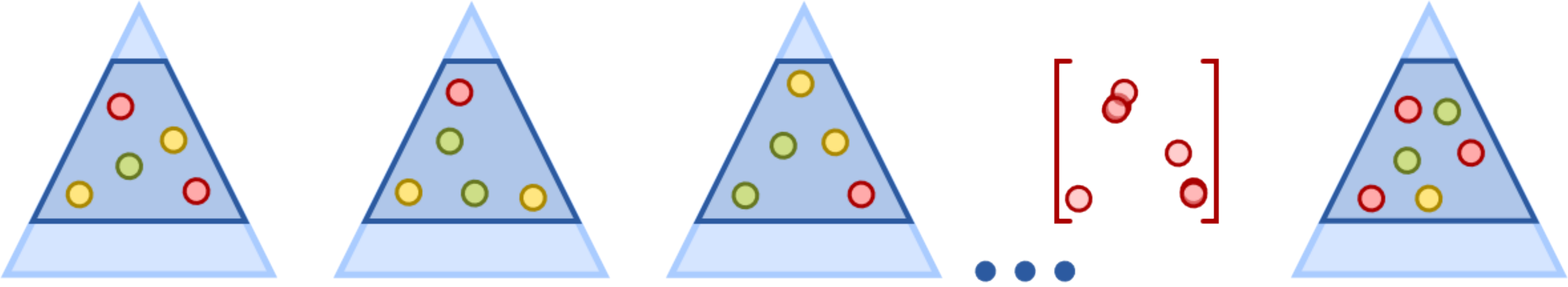
Integrate Multiple Hierarchies with a Trained Threat Classifier to Construct per Class Consensus Segmentation

- Train threat classifier using labeled data and a set of custom designed features, e.g., histograms, shape, volume, etc.
- Construct multiple hierarchical segmentations by randomizing the merge order
- Classify subset segments into four classes (saline, clay, rubber, nt)

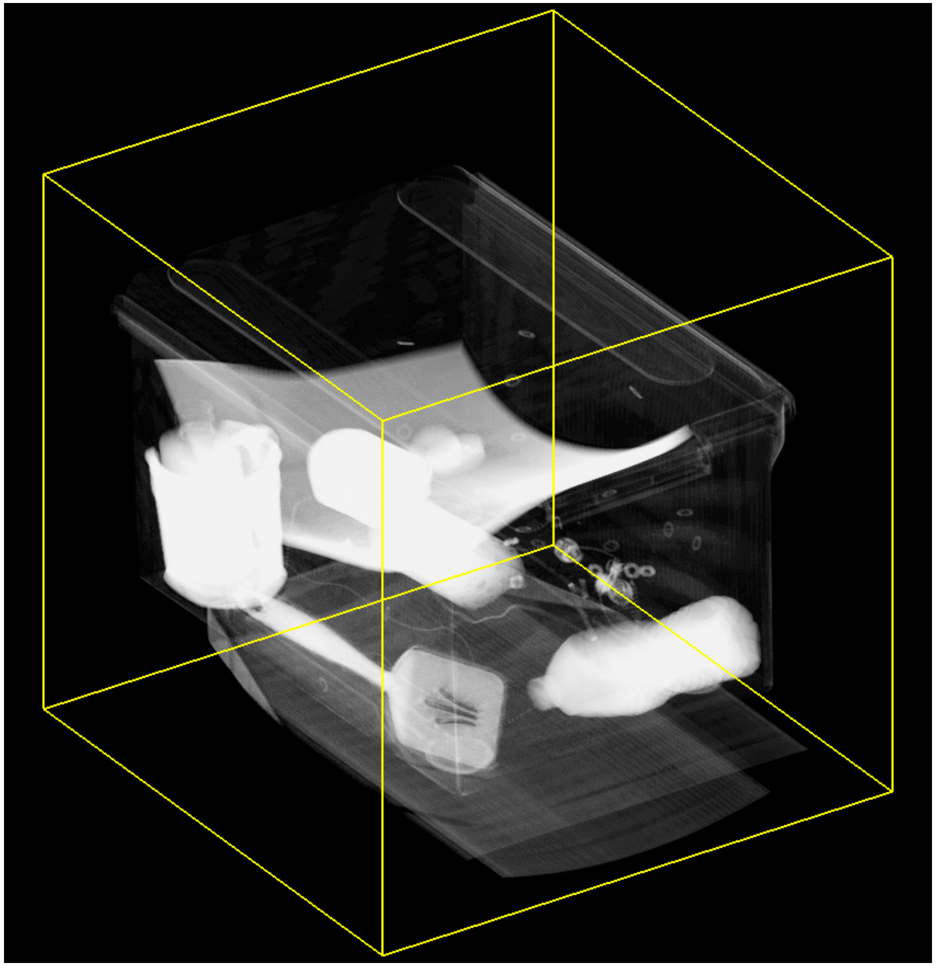


Integrate Multiple Hierarchies with a Trained Threat Classifier to Construct per Class Consensus Segmentation

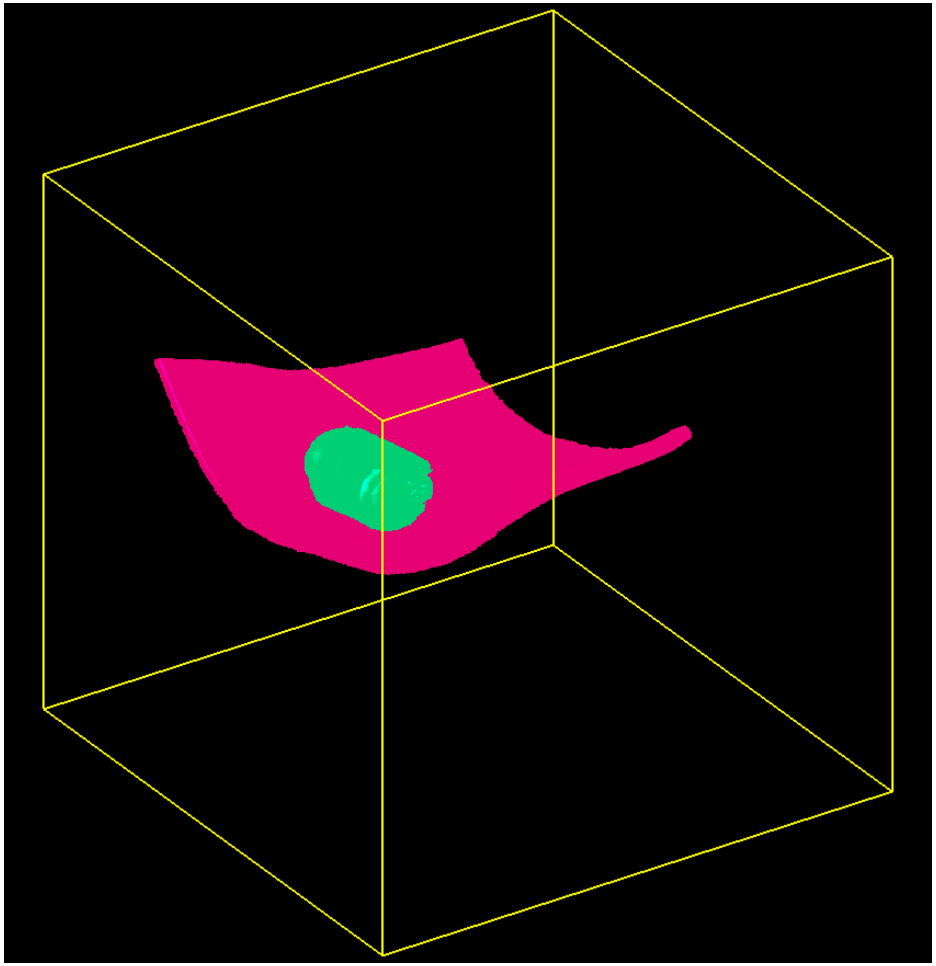
- Train threat classifier using labeled data and a set of custom designed features, e.g., histograms, shape, volume, etc.
- Construct multiple hierarchical segmentations by randomizing the merge order
- Classify subset segments into four classes (saline, clay, rubber, nt)
- Build consensus segmentation within each class to construct a per-object "best" segmentation



Results Using 20 Randomized Hierarchies – Bag 93

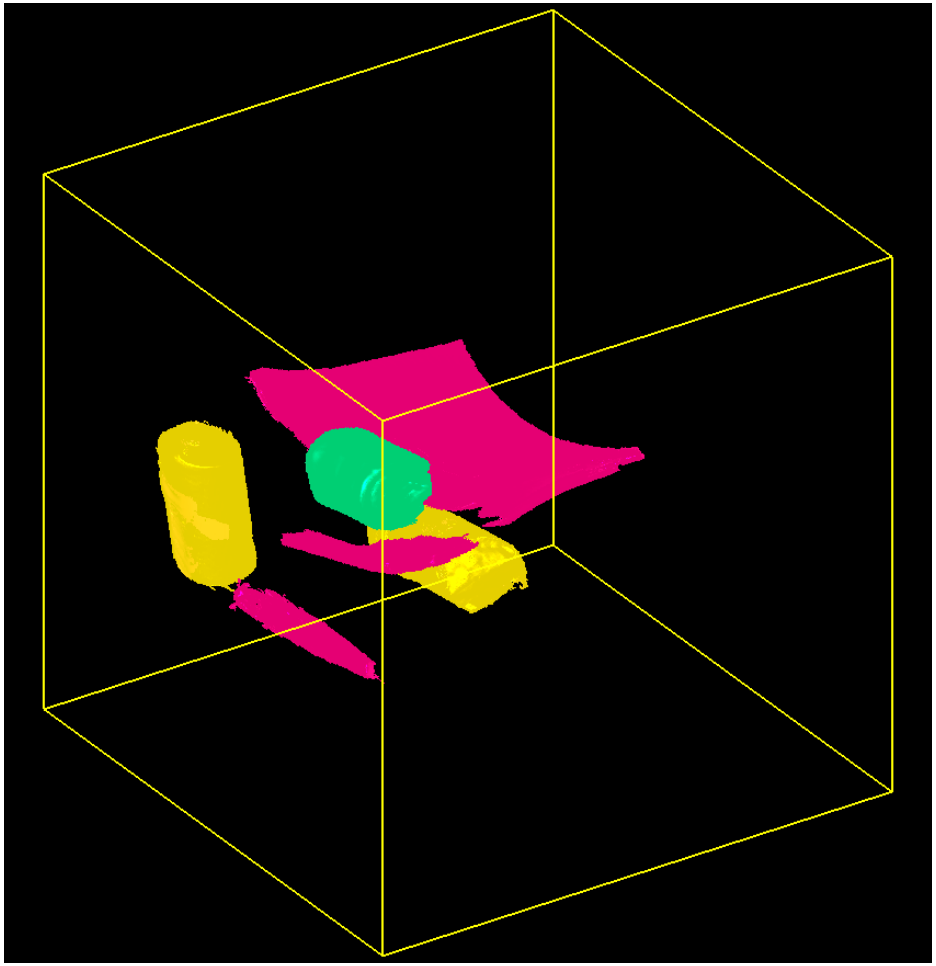


Volume rendering

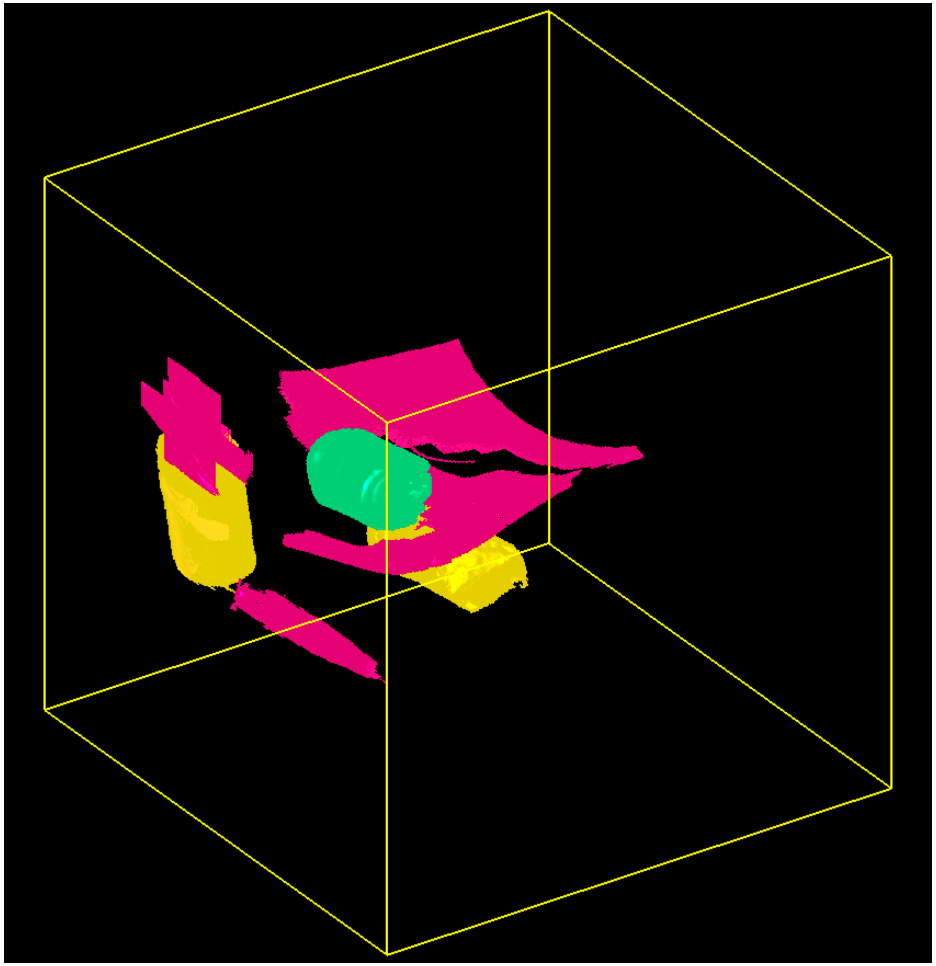


Human labeled data

Results Using 20 Randomized Hierarchies – Bag 93

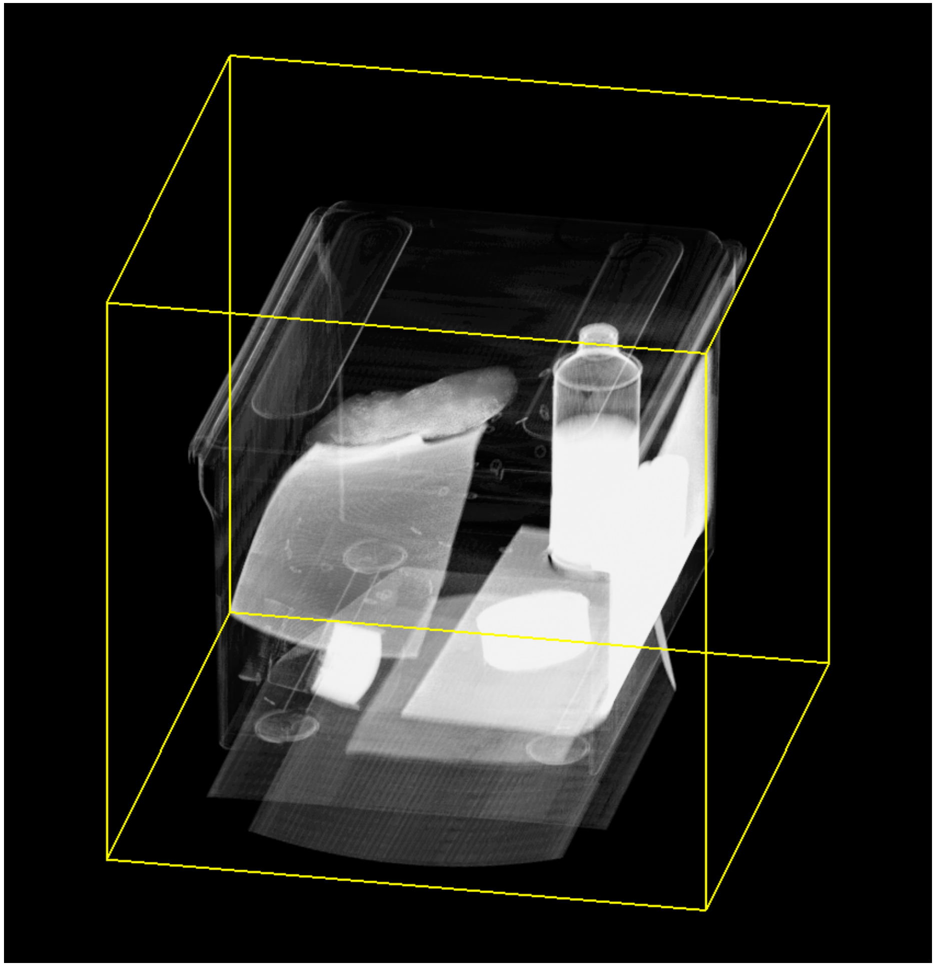


Multiple hierarchies

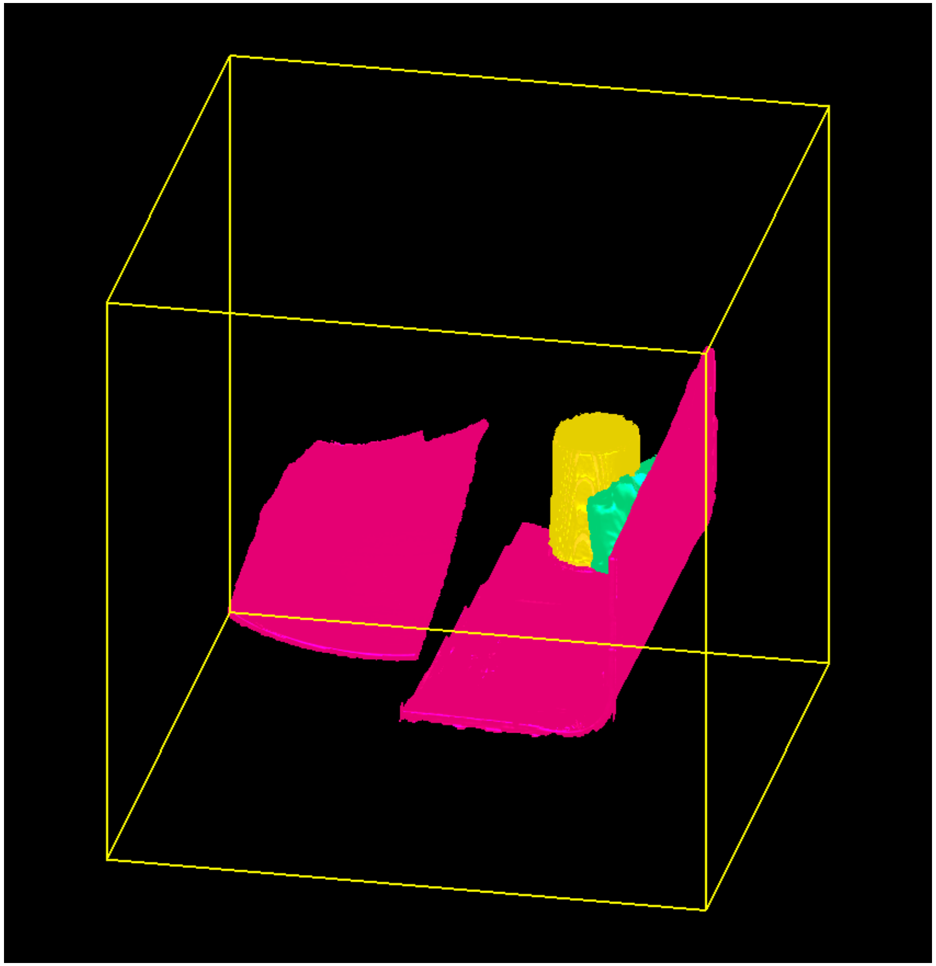


Single “best” hierarchy

Results Using 20 Randomized Hierarchies – Bag 80

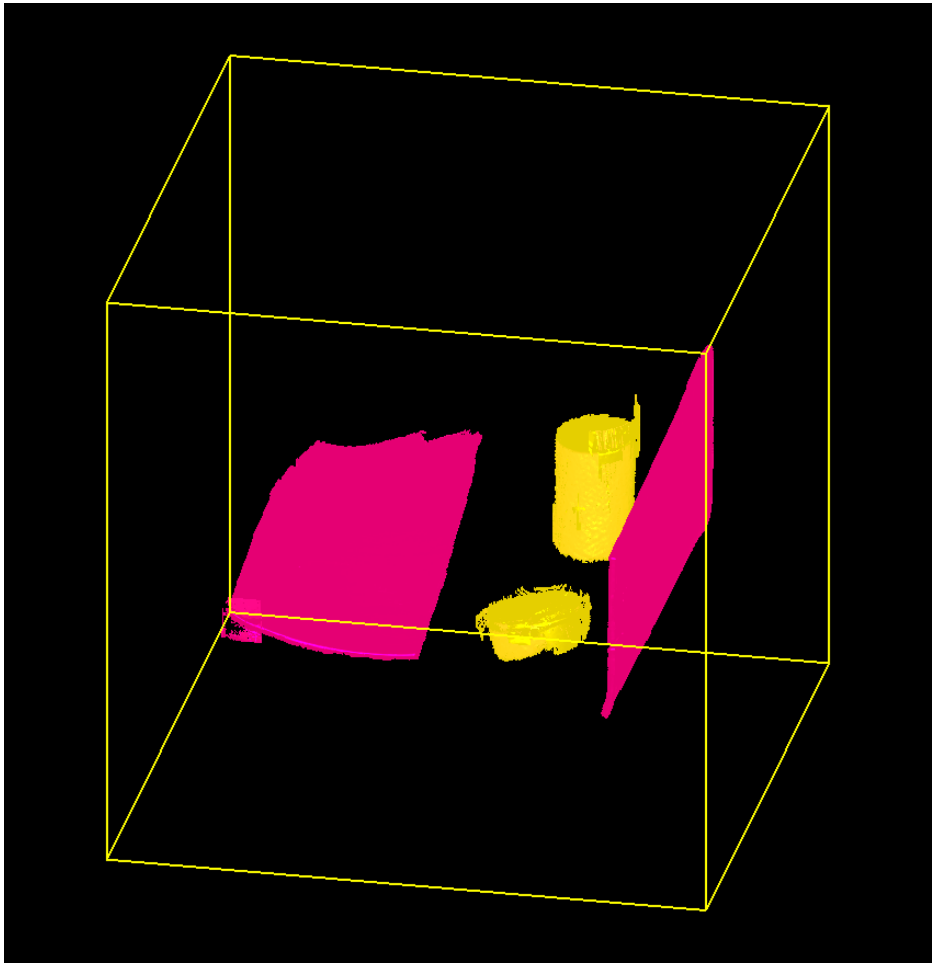


Volume rendering

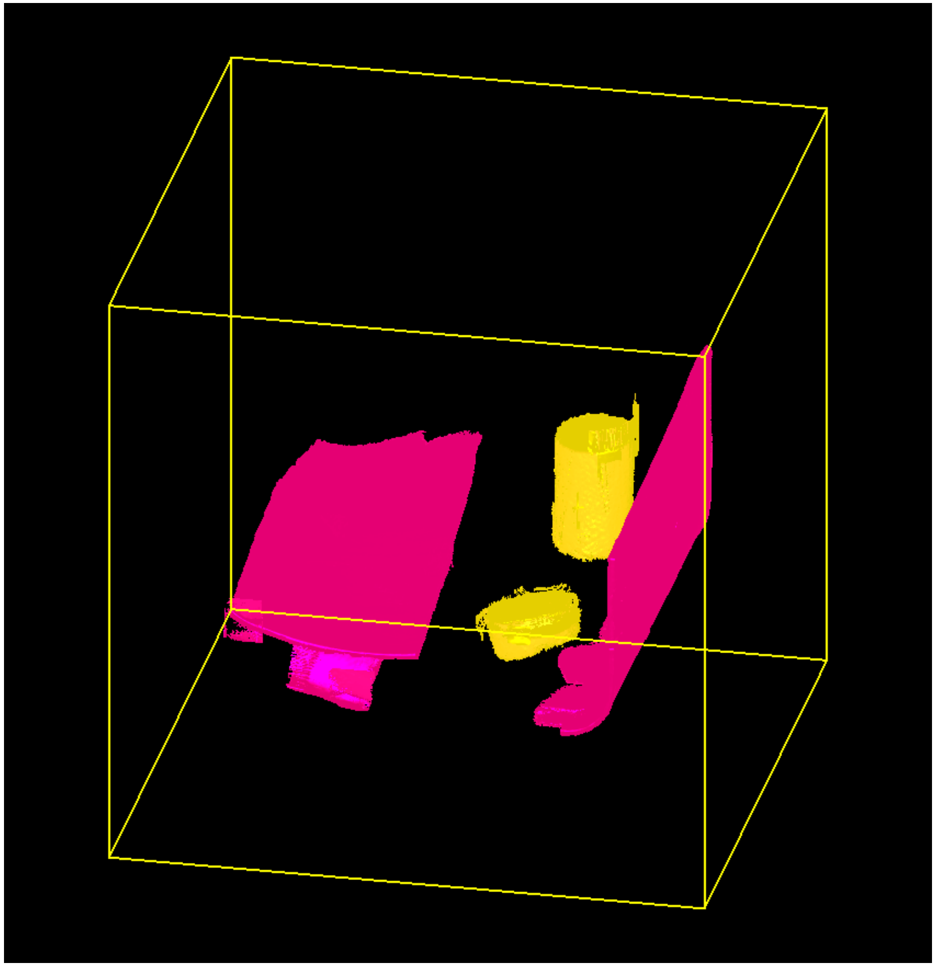


Human labeled data

Results Using 20 Randomized Hierarchies – Bag 93



Multiple hierarchies



Single "best" hierarchy

Segmentations based on Multiple Hierarchies Provide a Flexible Framework to Integrate Semantic Information

- Independent of the specific low or high level features
- Easy to construct though potentially expensive
- Expected to be robust against noise and artifacts
- Various opportunities to integrate semantic knowledge, i.e., to bridge the gap between *segmentation* and *detection*
- Promising results for natural images and luggage scans